EQUALIZATION OF SATELLITE MOBILE COMMUNICATION CHANNELS USING COMBINED SELF-ORGANIZING MAPS AND RBF NETWORKS.

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Abstract— **The paper proposes a neural network approach to equalize time varying nonlinear channels. The approach is applied to a satellite UMTS channel composed of time invariant linear filters, a non-linear memoryless amplifier and a time varying multipath propagation channel. The neural network equalizer has a Radial Basis Function structure. The usual k-mean clustering algorithm is replaced by a Kohonen learning rule. This results in an RBF-SOM equalizer which outperforms the LMS equalizer, and which has better recovering abilities (after passing through a high fading area) than the former RBF equalizer.**

I. Introduction

Neural Networks (NNs) have been used in many signal processing and communication applications (see e.g. [11] for a review). When compared to classical techniques, NNs display attractive behavior for digital communications. For example, NNs outperform classical techniques used for modelling nonlinear memoryless channels such as Travelling Wave Tubes (TWT) amplifiers [10]. Recently, NNs were used for identification and characterization of digital satellite channels [12]. Concerning the equalization problem, Multilayer Perceptron (MLP) were shown to be able to equalize non-minimum phase channels [2], and demonstrated good tracking abilities when used in multipath fading channels [1].

Recently, the Radial Basis Function (RBF) NN has been applied to the equalization problem because of its structural simplicity [3]. The RBF equalizer estimates the probability density function of the incoming signal in order to approximate the optimal Bayesian equalizer. It combines the supervised LMS algorithm with the blind k-mean clustering algorithm. This method proves to give good results when applied to simple non-linear channels [3][4]. However it converges much more slowly when the number of required neurons grows. In [8] a method was proposed to reduce the number of neurons of the RBF equalizer.

Independently, Self Organizing Maps (SOM) show great abilities to adaptively fit to any kind of random distribution without a priori information [5]. In [6] a SOM was used together with a Decision Feedback Equalizer (DFE) in order to improve the decision device. This system successfully equalized a non-linearly distorted channel.

This paper proposes to combine the RBF and SOM based equalizers by replacing the RBF k-mean algorithm with a Kohonen algorithm. The resulting algorithm was applied to the equalization of a satellite mobile communication channel. This kind of channel includes power amplifiers used near saturation which enhance important non-linear distortions.

The paper is organized as following. Section II briefly introduces RBF equalizers. Section III describes the RBF network combined with a Kohonen algorithm. Finally, Section IV provides computer simulation results to demonstrate the efficiency of this algorithm.

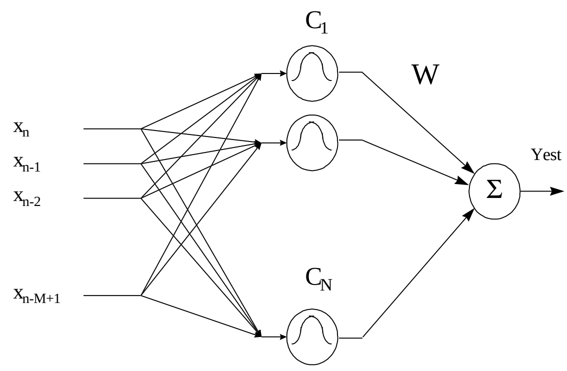

Fig. 1. Radial Basis Function Neural Network.

II. RBF Equalizer

RBF Networks have already been investigated as equalizers [7]. In [4] they are successfully applied to the equalization of simple non-linear channels. As depicted in Figure 1, the RBF network consists of 2 layers. Each neuron on the hidden layer computes the norm distance (usually Euclidean) between its center and the input vector (both M dimensional vectors), and passes the result through a non-linear function. The output response of the RBF network yields:

$$Y_{est} = \sum_{i=1}^{N} w_i e^{-\frac{\|X-C_i\|^2}{\sigma_i^2}}$$

where w_i are the complex weights of the output layer, C_i are the centers and σ_i is the spread parameter of the gaussians. The parameters of the RBF network are adapted with the recursive Hybrid Clustering algorithm :

- *Self-organized learning:* The nearest center from the input vector is moved in its direction (k-mean clustering algorithm):

$$\widetilde{k} = \arg(\min_k \|X(n) - C_k(n)\|)$$
$$C_k(n+1) = \begin{cases} C_k(n) + \mu\,[X(n) - C_k(n)] & \text{if } k = \widetilde{k} \\ C_k(n) & \text{otherwise} \end{cases}$$

- *Supervised learning:* The output layer weights are updated with the complex LMS algorithm:

$$w_k(n+1) = w_k(n) + \mu[d(n) - Y(n)].e^{-\frac{\|X - C_k\|^2}{\sigma_k^2}}$$

The centers of the neuron converge to the channel states. The channel states are the M dimensional possible outputs of the equivalent noiseless channel. The number of channel states may be referred to as the channel order.

III. An RBF Network Adapted with a Kohonen Algorithm

When the channel order increases, the number of required neurons becomes prohibitive and their convergence very erratic. Indeed many neurons may be "forgotten" by the k-mean algorithm (i.e. they almost never win) and others may oscillate between two or more channel states. The coefficients which correspond to the "forgotten" neurons converge to zero, and thus, the RBF network converges to a suboptimal equalizer.

If the input dimension is lower or equal to 3, it is possible to easily associate a *neighborhood function* to the RBF neurons. The neurons of the RBF are then regarded as a SOM. The neurons update equations follow the Kohonen learning rule:

$$\begin{array}{l} \widetilde{k} = \arg(\min_k \|X(n) - C_k(n)\|) \\ C_i(n+1) = C_i(n) + h_{\widetilde{k}i}(n)\,[X(n) - C_i(n)] \quad \forall i \in \{1, ..., N\} \end{array}$$

where $C_{\widetilde{k}}$ is the winning neuron, and $h_{ij}(n)$ is the so-called neighborhood kernel. This function must respect $h_{ij}(n) \to 0$ when $n \to \infty$ to ensure convergence. Nevertheless, as multipath fading channel equalization is considered, this function should not approach zero (it can be chosen time constant). This enables the network to adapt itself quickly when the channel characteristics vary.

In this paper, the study is restricted to a two dimensional input network (in Phase and Quadrature components of the incoming signal). The number of required neurons is then 4 if 4-QAM transmission is considered, and 16 if 16-QAM transmission is modulated. In both cases, the topological neighborhood is a grid, and the neighborhood kernel is set to α $(0 < \alpha \leq 1)$ on the diagonal, to approximately $\frac{\alpha}{5}$ for direct neighbors and to 0 otherwise. For the 4-QAM channel, it yields:

$$H = (h_{ij}) = \begin{pmatrix} \alpha & \alpha/5 & 0 & \alpha/5 \\ \alpha/5 & \alpha & \alpha/5 & 0 \\ 0 & \alpha/5 & \alpha & \alpha/5 \\ \alpha/5 & 0 & \alpha/5 & \alpha \end{pmatrix}$$

The architecture of an RBF-SOM equalizer is shown in Figure 2, in the case of a 4-QAM transmission.

The output layer complex coefficients are adapted with a complex LMS algorithm.

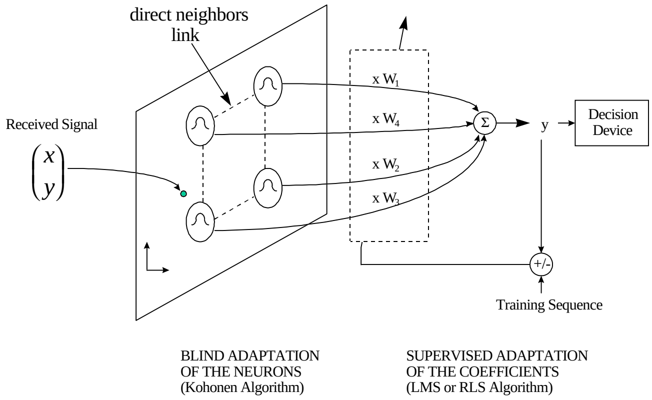

Fig. 2. SOM-RBF Equalizer

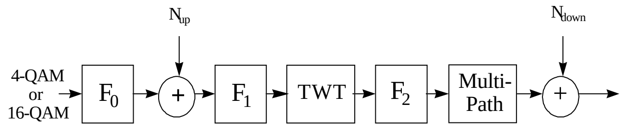

Fig. 3. Channel Description

IV. Simulation Results

A. Channel Description

Consider the baseband equivalent satellite mobile communication channel model given in Figure 3.

The channel characteristics are exposed below:

- MODULATION : 4-QAM or 16-QAM modulation, with 10 samples per symbol. A base-band transmission was simulated. The symbol rate is 30 Mbauds.
- FILTER $\mathrm{F_0}$: This emission filter is a four-pole Chebychev filter. Its 3dB bandwidth is $\frac{1.66}{T}$ (100 MHz), where T is the symbol duration.
- FILTER $\mathrm{F_1}$: The linear filter at the input of the satellite is a four-pole Chebychev filter. Its 3dB bandwidth is $\frac{2}{T}$ (120 MHz).
- NON-LINEAR AMPLIFIER : The TWT is defined by the analytic model of Saleh [9]. The non-linearity is memoryless because it only depends on the instantaneous power of the input signal. The amplitude gain and phase wrapping are :

$$\begin{array}{rcl} A(r) & = & \dfrac{2}{1+r^2} \\ \Phi(r) & = & \dfrac{4.0033r^2}{1+9.104r^2} \end{array}$$

where r is the norm of the sample passing through the TWT.

- FILTER $\mathrm{F_2}$ and MULTIPATH : $\mathrm{F_2}$ is a four-pole Chebychev filter. Its 3dB bandwidth is $\frac{3.3}{T}$ (200 MHz). It is followed by a 1-reflected-path multipath model. The adjustable parameters are the time delay τ_1 between the direct path and the reflected path, the attenuation of the reflected path and the speed of the mobile, which determines the shape of the Doppler spectrum of the multiplicative noise.

B. Results

In the following simulations, the multipath channel characteristics are: $\tau_1 = 10^{-7}s$, $5dB$ of attenuation between the direct path and the reflected path, mobile speed of $150km/h$.

As a first step, 4-QAM modulation is considered. Figure 4 gives the BER vs the down-link SNR, with an up-link SNR fixed to $15dB$. The RBF-SOM network performs better than the LMS equalizer at any level of down-link noise. As shown in Figure 5, the RBF-SOM keeps having better performance when crossing a high fading area.

Figure 6 shows a comparison between the classical RBF equalizer and the new RBF-SOM equalizer. Both equalizers

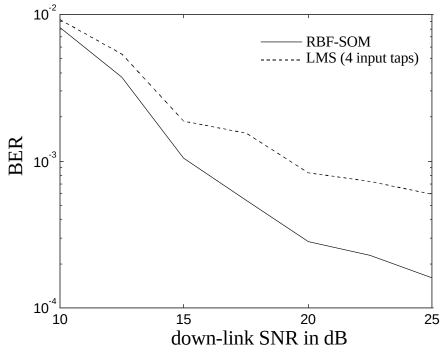

Fig. 4. BER vs SNR: Comparison between the RBF-SOM and a Tapped Delay Line adaptated with the LMS. Up-link SNR = 15dB

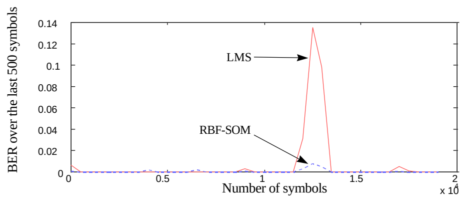

Fig. 5. Evolution of the BER : Comparison between the RBF-SOM and the LMS.

perform as well as long as the topology of the centers remain stable (e.g. in low fading area). However, the RBF-SOM equalizer recovers much more quickly after crossing high fading areas.

The aforementioned phenomena are more sensitive for the 16-QAM channel, because it becomes much more difficult to recover the right topology after a fading hole or during initialization. Figure 7 compares the behavior of a classical RBF with the RBF-SOM, after a few iterations. The RBF-SOM centers have already converged to an acceptable topology, whereas the classical RBF centers have not.

V. Conclusion

The paper proposed a method to improve the RBF equalizer resorting to SOM. A typical example of satellite UMTS channel has been presented. Simulation results proved the RBF-SOM equalizer to provide better BER performance than the RBF equalizer in presence of multipath fading conditions. This improvement is all the more sensitive as the number of symbols in the modulation scheme grows.

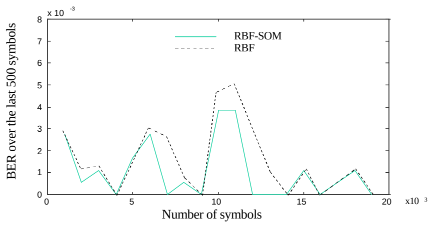

Fig. 6. Evolution of the BER : Comparison between the RBF-SOM and the RBF (mobile speed 300km/h).

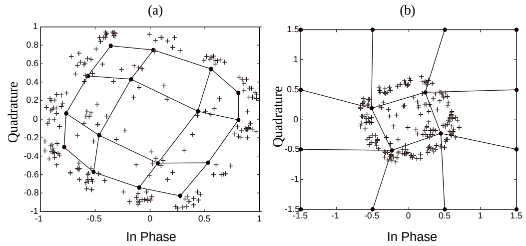

Fig. 7. 16-QAM Received symbols and Centers : (a) RBF-SOM, (b) RBF.

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